An Autonomous Neuro-Symbolic Framework for Verified Legacy Code Modernization at Planetary Scale

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PART I: THE VISION AND THE PROBLEM

Chapter 1: Prologue

In the year 2026, humanity faces an invisible crisis. Buried within the digital infrastructure of civilization lies approximately 800 billion lines of COBOL code . This code processes your credit card transactions, calculates your tax refunds, approves your mortgage applications, tracks your airline baggage, and manages the social security payments that keep millions of elderly citizens alive .

This code was written largely between 1965 and 1995. The engineers who wrote it are retired or deceased. The languages it uses—COBOL, FORTRAN, PL/I, RPG—are no longer taught in universities . Yet 68% of all production workloads still run on mainframes, many of them dependent on this decades-old code .

This is not merely a technical debt. It is a civilizational debt. And it is coming due.

When a major European automotive manufacturer attempted to modernize 15 million lines of COBOL code, they discovered that reverse engineering just 10,000 lines required six weeks of work by two full-time engineers plus a subject matter expert . At

that rate, modernizing the world's 800 billion lines of legacy code would require approximately 9.2 million person-years—roughly the entire global software engineering workforce working exclusively on this problem for the next 50 years.

We do not have 50 years. We do not have 50,000 specialized COBOL engineers. What we have, for the first time in human history, is something else: artificial intelligence systems capable of understanding, reasoning about, and transforming code.

This paper proposes a solution that does not merely incrementally improve existing approaches. It proposes a fundamental reimagining of how humanity will transition its digital infrastructure from the 20th century to the 22nd century. It proposes a framework that combines the pattern-matching power of large language models with the mathematical certainty of formal verification, orchestrated by autonomous multi-agent systems that work at scales previously unimaginable.

The result is not just a research paper. It is a roadmap for the largest software engineering project in human history—a project that must succeed if civilization's digital foundation is not to crumble under its own weight.

Chapter 2: The Scale of the Crisis

2.1 The Quantitative Dimension

To understand why this problem demands extraordinary solutions, we must first grasp its extraordinary scale. Consider these numbers, each representing a facet of the crisis:

Dimension	Magnitude	Implication
Total COBOL lines in production	800 billion	If printed as books, would fill the Library of Congress 50,000 times
Workloads running on mainframes	68% of enterprise production	The global economy runs on machines designed in the 1960s
Cost to maintain legacy systems	$1.3 trillion annually	Equivalent to the GDP of Australia, spent just on keeping old systems running
COBOL engineers available	Fewer than 50,000 globally	One engineer for every 16 million lines of code
Time to reverse engineer 10,000 lines	6 weeks (manual)	At this rate, 800 billion lines would take 9.2 million person-years
Modernization project failure rate	>65%	Most attempts to migrate legacy systems fail entirely

These numbers tell a stark story. The traditional approach—assembling teams of experts to manually understand, document, and rewrite legacy code—simply cannot scale to meet the need. It is mathematically impossible.

2.2 The Qualitative Dimension: Why Legacy Code Is So Hard to Modernize

Numbers alone, however, fail to capture the true nature of the challenge. Legacy code is not merely old code. It is code that embodies decades of accumulated business knowledge, much of it undocumented and some of it understood by no living person .

Consider a typical COBOL program written for a bank in 1978. It contains:

1. Business rules that encode regulatory requirements from five different decades
2. Workarounds for hardware limitations that no longer exist
3. Optimizations for data formats that were standard in the 1970s
4. Error handling for conditions that may never occur but must still be preserved
5. Temporal logic that assumes certain operations complete within specific time windows
6. Data dependencies on file structures that have been modified dozens of times
7. Undocumented features that have become de facto standards over 40 years

An engineer approaching this code faces what researchers call the "archaeological problem" : they must reconstruct not only what the code does, but why it does it, and which of its behaviors are essential versus accidental.

The challenge is compounded by the fact that these systems are often mission-critical. A bank cannot simply shut down its core transaction processing system for six months while engineers figure out how it works. A government cannot stop sending Social Security checks while its COBOL systems are being modernized. The systems must continue running correctly throughout the modernization process.

2.3 The Human Dimension: The Vanishing Experts

Perhaps the most urgent dimension of the crisis is demographic. The engineers who built these systems are aging out of the workforce. According to industry estimates, the average age of a mainframe COBOL programmer is over 55 . Every day, dozens of these experts retire, taking with them decades of undocumented knowledge about how critical systems actually work.

This creates a knowledge extinction event. When a COBOL expert retires, their understanding of the code they maintained—the subtle bugs they fixed, the edge cases they discovered, the reasons behind seemingly arbitrary constants—is lost forever. The code remains, but the context that explains it vanishes.

Modernization efforts that rely on these experts become increasingly difficult each year. The window of opportunity to capture this knowledge is closing rapidly. Within a decade, there will be virtually no one left who understands the foundational systems of the global economy .

Chapter 3: The State of the Art — What Exists Today

Before we can propose a revolutionary solution, we must understand the current landscape. The field of AI-assisted legacy code modernization has advanced significantly in the past two years, and several approaches have demonstrated promising results.

3.1 Multi-Agent LLM Systems

The most sophisticated current approaches use multi-agent systems where multiple AI models collaborate, each playing a specialized role. The VAPU (Verifying Agent Pipeline Updater) system, developed by Ala-Salmi and colleagues, represents a significant advance in this direction .

VAPU simulates a software development team using multiple LLM agents with distinct roles:

- Architect agents that understand system structure
- Developer agents that implement changes
- Tester agents that validate outputs
- Reviewer agents that check for quality

In evaluations on legacy web application view files, VAPU achieved up to 22.5% improvement in successful file updates compared to standard prompting approaches . The system demonstrated that distributing responsibility across specialized agents produces better results than asking a single model to handle entire modernization tasks.

However, VAPU has significant limitations. Its evaluation focused primarily on web applications rather than the COBOL and FORTRAN mainframe systems that constitute the bulk of legacy code. More importantly, while VAPU can generate working code, it cannot guarantee correctness—a critical requirement for mission-critical financial and governmental systems.

3.2 Domain-Specific Translation Systems

Another line of research focuses on translating code between specific languages and frameworks. Gupta and colleagues at Los Alamos National Laboratory developed an agentic AI workflow for translating legacy FORTRAN to Kokkos C++ .

This work is particularly significant because it addresses high-performance computing (HPC) code, where correctness and performance are both critical. The Los Alamos system achieved:

- Fully autonomous kernel translation for under $3.50 per kernel
- Successful porting of FORTRAN benchmarks to GPU-accelerated platforms
- Performance improvements over the original FORTRAN baselines

The researchers found that proprietary models significantly outperformed open-source alternatives, with models like GPT-5 and o4-mini-high succeeding where Llama4-Maverick failed .

This work demonstrates that agentic AI systems can handle the complexity of scientific code, but it also reveals the current limitations: the approach works well for individual kernels but struggles with entire applications, and it lacks formal verification of correctness.

3.3 Formal Verification Approaches

At the opposite end of the spectrum from pure LLM approaches are systems based on formal verification. Code Metal's Tenspiler and LLMLift systems represent this approach, combining program synthesis with mathematical proof techniques .

Tenspiler uses a technique called "verified lifting" to transform legacy C/C++ code into domain-specific languages for modern hardware. The system:

1. Searches for a target-language program equivalent to the source
2. Verifies the equivalence using formal methods
3. Generates the transformed code only when equivalence is proven

The advantage of this approach is absolute correctness guarantees. When Tenspiler successfully transforms code, the result is mathematically proven to behave identically to the original.

However, Tenspiler's formal search approach has severe scalability limitations. The search space grows exponentially with program complexity, and even with sophisticated pruning optimizations, the system becomes intractable for large programs . The researchers manually wrote approximately 1,200 lines of optimization code just to make the system work for moderately sized examples—an approach that cannot scale to millions of lines of code.

3.4 Hybrid Neuro-Symbolic Systems

Recognizing the limitations of both pure LLM and pure formal approaches, some researchers have begun exploring hybrid neuro-symbolic systems. Code Metal's LLMLift, developed in collaboration with UC Berkeley, represents the state of the art in this direction .

LLMLift uses:

- LLMs with few-shot prompting to generate program summaries and loop invariants
- Python as an intermediate representation to leverage LLMs' training on modern languages
- Formal verification tools to prove the equivalence of source and transformed code

The key insight is that LLMs excel at generating plausible candidates, while formal methods excel at verifying correctness. By combining them, LLMLift achieves both scalability and correctness guarantees.

Early results are promising, but the system is still experimental and has only been tested on relatively small programs. Scaling to millions of lines of real-world COBOL remains an open challenge.

3.5 Commercial Solutions and Real-World Impact

Several companies have begun deploying AI-powered modernization tools in production environments. Crowdbotics uses AI to create "digital twins" of codebases, reducing analysis time from months to hours . Thoughtworks' CodeConcise combines abstract syntax trees with knowledge graphs to accelerate reverse engineering, achieving a 66% reduction in time for automotive mainframe modernization .

The CodeConcise case study is particularly instructive. Working with a manufacturer facing a 15-million-line COBOL modernization deadline, Thoughtworks:

- Used ASTs to extract logical units and dependencies
- Built a knowledge graph to visualize relationships
- Applied RAG (Retrieval-Augmented Generation) to answer questions about code

- Reduced reverse engineering from 6 weeks to 2 weeks per 10,000-line module

The projected savings: 60,000 person-days across the entire modernization effort .

Another commercial effort, documented in a 2025 paper, achieved 93% accuracy in translating COBOL to Java, with complexity reductions of 35% and coupling reductions of 33%—significantly outperforming both manual efforts (75% accuracy) and rule-based tools (82%) .

3.6 Autoformalization and Verification

A fascinating parallel line of research involves autoformalization—using LLMs to translate natural language specifications into formal mathematical languages. The "FormalizeWithTest" project demonstrates that LLMs can generate formal specifications in Lean that can be verified against test cases .

This approach has direct relevance to legacy code modernization. If we can autoformalize the implicit specifications embedded in legacy code, we can verify that transformed code preserves those specifications. The project showed that approximately 10 out of 17 translated problems passed formal verification, with another 6 unproven and only 1 proven false .

This suggests that autoformalization is viable but not yet reliable—exactly the kind of problem where hybrid approaches combining LLMs with formal methods are most promising.

3.7 Gaps and Limitations

Despite these advances, significant gaps remain:

Gap	Description	Why It Matters
Scale	Current systems handle thousands of lines, not millions	Real-world modernization requires processing entire systems
Verification	Most systems lack correctness guarantees	Financial and governmental systems cannot accept errors
Preservation of intent	Systems capture what code does, not why	Lost business knowledge cannot be reconstructed
Performance equivalence	Few systems verify performance characteristics	Real-time systems require predictable performance
Human collaboration	Systems replace humans rather than augmenting them	The goal should be to multiply human expertise, not eliminate it
Evolutionary modernization	Most approaches assume "big bang" replacement	Systems must evolve incrementally while running

PART II: THE PROPOSED SOLUTION

Chapter 4: The HADES Framework

We propose the HADES Framework (Hierarchical Autonomous Decompilation and Evolution System)—a comprehensive neuro-symbolic architecture for planetary-scale legacy code modernization. HADES is not merely an incremental improvement over existing systems. It represents a fundamental reconceptualization of how legacy systems should be understood, transformed, and evolved.

4.1 Core Principles

The HADES framework is built on eight core principles:

Principle 1: Preservation of Intent, Not Just Behavior
The goal is not merely to produce code that behaves identically to the original. It is to capture and preserve the *intent* behind the code—the business rules, the regulatory requirements, the domain knowledge that the code embodies. This intent must be made explicit and carried forward into the modernized system.

Principle 2: Verified Correctness
Every transformation must be accompanied by a mathematical proof of semantic equivalence. For mission-critical systems, "works most of the time" is not acceptable. HADES will incorporate formal verification at every stage, ensuring that transformed code is provably equivalent to the original.

Principle 3: Human-AI Collaboration
Rather than attempting fully autonomous modernization, HADES is designed to augment human expertise. It captures knowledge from subject matter experts, learns from their judgments, and gradually reduces their required involvement. The goal is to multiply human capability, not replace it.

Principle 4: Incremental Evolution
Legacy systems cannot be taken offline for modernization. HADES supports incremental transformation, allowing modernized components to coexist with legacy components during the transition. Systems evolve continuously rather than being replaced in "big bang" migrations.

Principle 5: Multi-Agent Orchestration
Modernization requires diverse capabilities: code understanding, specification inference, transformation, verification, testing, optimization, and documentation. HADES employs specialized agents for each capability, coordinated by a meta-agent that manages the overall process.

Principle 6: Knowledge Graph Foundation
All knowledge about the system—code structure, dependencies, business rules, regulatory requirements, expert insights—is captured in a unified knowledge graph. This graph serves as the system's memory, enabling reasoning across the entire codebase.

Principle 7: Autoformalization of Specifications
The implicit specifications embedded in legacy code are made explicit through autoformalization into languages like Lean, Coq, or Dafny. These formal specifications become the basis for verification and the bridge between legacy and modernized code.

Principle 8: Continuous Learning
HADES learns from every interaction. When experts correct its outputs, when transformations fail verification, when tests reveal edge cases—these experiences improve the system's future performance. HADES becomes more capable over time, not less.

4.2 The HADES Architecture

The HADES architecture consists of five interconnected layers, each building on the capabilities of the layers below.

Layer 1: Code Ingestion and Analysis Layer

This layer is responsible for ingesting legacy code and building an initial understanding. It comprises:

Multi-Language Parser Framework: Supports all major legacy languages: COBOL (multiple dialects), FORTRAN (multiple standards), PL/I, RPG, Assembly, and others. Produces language-agnostic abstract syntax trees.

Dependency Analysis Engine: Traces dependencies across the codebase: data dependencies, control dependencies, call graphs, file dependencies, transaction flows. Builds a complete map of system structure.

Static Analysis Suite: Performs traditional static analysis to identify code smells, complexity hotspots, dead code, and security vulnerabilities.

Pattern Discovery Module: Uses unsupervised learning to identify recurring patterns in the code: common idioms, standard error handling, data validation patterns. These patterns become candidates for standardized transformation.

Legacy Knowledge Base: Contains knowledge about legacy language quirks, platform-specific behaviors, historical standards, and known patterns. This knowledge informs the analysis and guides transformation decisions.

Layer 2: Knowledge Graph Layer

The knowledge graph is the central repository for all information about the legacy system. It includes:

Structural Graph: Represents code structure: programs, subroutines, data structures, variables, control flow, data flow.

Semantic Graph: Captures meaning: business rules inferred from code, data semantics, transaction semantics, domain concepts.

Dependency Graph: Tracks all dependencies across the system, enabling impact analysis for proposed changes.

Evolution Graph: Records the system's history: when code was added, modified, or deleted; what changes were made; why changes were made (when available).

Expert Knowledge Graph: Captures knowledge from subject matter experts: explanations of complex code, rationales for design decisions, warnings about edge cases.

Formal Specification Graph: Stores formal specifications of code behavior, linked to the code elements they specify.

The knowledge graph uses a property graph model with rich semantic typing. It supports graph queries, path analysis, and graph neural network inference.

Layer 3: Specification Inference Layer

This layer is responsible for inferring formal specifications from legacy code. It includes:

Behavioral Specification Inference: Uses dynamic analysis (when test harnesses exist) and symbolic execution to infer input-output relationships. Learns preconditions, postconditions, and invariants.

Business Rule Extraction: Applies NLP to code identifiers, comments, and documentation to infer business rules. Cross-references these inferences with expert knowledge.

Data Semantic Inference: Infers the meaning of data structures: what fields represent, what constraints apply, what relationships exist between data elements.

Temporal Property Inference: Infers timing constraints, sequence requirements, and other temporal properties from code patterns.

Autoformalization Engine: Translates inferred specifications into formal languages. Uses LLMs with few-shot prompting, guided by the FormalizeWithTest approach , to generate specifications in Lean, Coq, Dafny, or other verification languages.

Specification Validation: Validates inferred specifications against test cases (when available) and against expert knowledge. Flags uncertain specifications for human review.

Layer 4: Transformation and Verification Layer

This layer performs the actual code transformation and verifies its correctness. It includes:

Transformation Planning Engine: Determines the optimal transformation strategy for each component. Considers: target language/platform, performance requirements, dependencies, transformation complexity, risk factors.

Multi-Agent Transformation System: Deploys specialized agents for different transformation tasks:

Agent Type	Responsibility
Architect Agent	Determines how components should be restructured for the target architecture
Translator Agent	Performs source-to-source translation between languages
Optimizer Agent	Optimizes transformed code for target platform performance
Data Agent	Handles data structure and database transformations
Interface Agent	Manages interfaces between transformed and legacy components

Formal Verification Engine: Proves semantic equivalence between source and transformed code. Uses:

- Theorem proving (when specifications are available)
- Model checking (for control-intensive components)
- Symbolic execution (for data-intensive components)
- Equivalence checking (for structurally similar code)
- Proof assistants (Lean, Coq, Isabelle) for critical components

Test Generation and Execution: Generates test suites from specifications and runs them on transformed code. Uses property-based testing to explore edge cases.

Performance Validation: Measures and validates performance characteristics of transformed code against requirements.

Incremental Integration Manager: Manages the integration of transformed components into the evolving system. Handles versioning, compatibility, and rollback.

Layer 5: Human Collaboration and Learning Layer

This layer manages interaction with human experts and enables continuous learning. It includes:

Expert Knowledge Capture Interface: Provides tools for experts to document their knowledge: code annotations, explanations, warnings, rationales. Uses AI to suggest documentation opportunities and to validate expert inputs.

Query and Explanation System: Enables experts to ask questions about the code and receive explanations: "Why does this module handle dates this way?" "What are the dependencies of this transaction?" Uses the knowledge graph and RAG to answer questions .

Review and Validation Workflow: Manages the process of human review for AI-generated transformations. Preserves reviewer feedback for system learning.

Training Data Generation: Creates high-quality training data from successful transformations and expert corrections. This data is used to fine-tune models for improved performance.

Continuous Learning Pipeline: Retrains models periodically using accumulated data. Tracks system performance over time to identify improvement opportunities.

4.3 The Multi-Agent Orchestration Model

At the heart of HADES is a sophisticated multi-agent orchestration system, inspired by VAPU and the Los Alamos agentic workflow , but significantly extended.

The orchestration model uses a hierarchical swarm architecture:

Meta-Agent: The top-level coordinator. Maintains the overall plan, tracks progress, handles exceptions, and allocates resources. Communicates with domain agents to assign tasks and receive status.

Domain Agents: Specialized agents for different aspects of modernization. Each domain agent manages a fleet of worker agents in its domain.

Worker Agents: Perform specific tasks under domain agent supervision. Worker agents can be LLM-based, rule-based, or hybrid.

Specialist Agents: Provide specialized services to other agents: formal verification, test generation, performance analysis, etc.

The orchestration follows a plan-do-check-act cycle:

1. Plan: Meta-agent decomposes the overall modernization into tasks, assigns them to domain agents, and defines success criteria.
2. Do: Domain agents execute tasks using their worker fleets, monitoring progress and handling issues.
3. Check: Verification agents validate results. Specialist agents perform analysis.
4. Act: Meta-agent integrates verified results, updates the plan, and initiates next cycle.

This model enables massively parallel modernization while maintaining coordination and ensuring correctness.

Chapter 5: The Technical Innovations That Make HADES Revolutionary

HADES is not merely an assembly of existing techniques. It introduces several fundamental innovations that together enable capabilities beyond current systems.

Innovation 1: Neurosymbolic Specification Inference

Current systems either ignore specification inference (assuming it's unnecessary) or attempt purely formal approaches that don't scale. HADES introduces a neurosymbolic approach that combines the pattern recognition capabilities of LLMs with the rigor of formal methods.

How it works:

1. LLMs analyze code and generate candidate specifications in natural language
2. These candidates are translated into formal languages using autoformalization
3. Formal verification tools attempt to prove the candidates against the code
4. Candidates that cannot be proven are refined or discarded
5. The remaining candidates become verified specifications

This approach leverages LLMs' ability to understand code semantics while using formal verification to ensure correctness. It scales because LLMs can generate plausible candidates quickly, and verification need only check (rather than discover) specifications.

Novelty: No existing system combines LLM-based specification inference with formal verification at this scale. The closest approach, LLMLift , focuses on transformation rather than specification inference.

Innovation 2: The Living Knowledge Graph

Most code analysis systems build static representations that become obsolete as soon as the code changes. HADES introduces a living knowledge graph that evolves with the system and learns from every interaction.

Key features:

- Continuous update: The graph updates automatically as code changes
- Multi-modal representation: Code structure, semantics, dependencies, history, and expert knowledge are integrated in a single graph

- Graph neural network embeddings: Code elements are embedded in vector spaces that enable similarity search, anomaly detection, and pattern discovery
- Temporal versioning: The graph preserves history, enabling analysis of how the system evolved
- Explanation traces: When experts explain code, their explanations are linked to graph elements, creating a knowledge base that grows over time

Novelty: While knowledge graphs have been used in code analysis , HADES's living knowledge graph is unique in its integration of multiple knowledge types, its continuous learning capability, and its use as the foundation for all downstream reasoning

Innovation 3: Multi-Level Formal Verification

Existing verification approaches operate at a single level: either verifying individual functions or verifying entire systems. HADES introduces multi-level verification that provides correctness guarantees at every level of abstraction.

The verification hierarchy:

Level	What is Verified	Method
Unit	Individual functions/modules	Equivalence checking, theorem proving
Component	Collections of related modules	Compositional verification
Interface	Interactions between components	Contract verification

Data	Data structure invariants	Invariant checking
Transaction	End-to-end business transactions	Temporal logic model checking
System	Overall system behavior	Simulation, property checking

Verification at higher levels builds on verified lower levels, creating a chain of trust from individual lines of code to entire systems.

Novelty: No existing system provides integrated verification across all these levels. Most focus on either low-level equivalence or high-level properties, but not both.

Innovation 4: Incremental Transformation with Runtime Verification

Traditional modernization approaches require systems to be taken offline for transformation. HADES introduces incremental transformation with runtime verification, enabling systems to evolve continuously while running.

How it works:

1. The system is instrumented to capture runtime behavior
2. Transformed components run in parallel with legacy components
3. Runtime verification compares behavior of legacy and transformed components
4. Differences trigger analysis and potential rollback
5. When confidence is sufficient, traffic is gradually shifted to transformed components

This approach, inspired by canary deployments and A/B testing, enables risk-free modernization of even the most critical systems. If a transformation introduces errors, the system automatically reverts to the legacy component with no user impact.

Novelty: While incremental modernization is discussed in industry , HADES's integration of runtime verification with formal methods creates unprecedented safety guarantees.

Innovation 5: The Expert Amplification Loop

Most AI systems treat humans as either supervisors (providing oversight) or data sources (providing training examples). HADES introduces the expert amplification loop, where experts and AI collaborate synergistically.

The loop:

1. AI analyzes code and generates questions for experts
2. Experts answer questions, providing knowledge
3. AI uses answers to improve its understanding
4. AI generates more sophisticated questions
5. Experts provide deeper knowledge
6. The cycle continues, with each iteration reducing expert effort while increasing system capability

This approach recognizes that the true value of experts is not in performing routine analysis (which AI can do) but in providing deep domain knowledge that cannot be extracted from code alone. By focusing expert attention on the most valuable knowledge transfer opportunities, HADES amplifies their impact.

Novelty: No existing system systematically engages experts in this kind of collaborative knowledge discovery loop.

PART III: EXPERIMENTAL VALIDATION AND RESULTS

Chapter 6: Experimental Design and Benchmark Suite

To validate HADES, we designed a comprehensive experimental program targeting the system's capabilities across multiple dimensions.

6.1 Benchmark Suite

We constructed a benchmark suite representing the full spectrum of legacy code challenges:

Benchmark	SL	Size (logs)	Domain	Key Challenges
COBOL-Banking-1	COBOL (OS/VS)	25,000	Core banking	50-year evolution, regulatory complexity, undocumented business rules
COBOL-Banking-2	COBOL (COBOL/II)	85,000	Mortgage processing	Complex calculations, date logic, interest computations
FORTRAN-Physics	FORTRAN 77	15,000	Scientific computing	Numerical methods, performance-critical loops
FORTRAN-Weather	FORTRAN 90	120,000	Weather modeling	MPI parallelism, complex I/O, real-time constraints

PLI-Inventory	PL/I	40,000	Inventory management	Complex data structures, file handling, batch processing
RPG-Manufacturing	RPG III	30,000	Manufacturing control	Report generation, screen handling, legacy database
Mixed-Legacy	Multiple	250,000	Enterprise system	Language mixing, cross-language calls, shared data

Each benchmark includes:

- The original source code
- Documentation (where available)
- Test suites (where available)
- Expert knowledge (captured from retired engineers for a subset)
- Known issues and edge cases

6.2 Baseline Systems

We compare HADES against multiple baselines:

Baseline	Type	Description
Manual	Human	Professional developers with legacy experience
VAPU	Multi-agent LLM	State-of-the-art multi-agent system
Los Alamos Agentic	Agentic workflow	Specialized for FORTRAN-to-Kokkos
LLMLift	Neuro-symbolic	Combines LLMs with formal verification
Commercial	Commercial	Crowdbotics, Thoughtworks CodeConcise

6.3 Evaluation Metrics

We evaluate systems across multiple dimensions:

Correctness Metrics:

- Semantic equivalence: Percentage of transformed code proven equivalent to original
- Test pass rate: Percentage of tests passed by transformed code

- Edge case preservation: Ability to handle known edge cases
- Regression rate: New bugs introduced during transformation

Productivity Metrics:

- Time to transform: Person-hours per 10,000 lines
- Expert hours required: Expert time needed for supervision
- Cost per line: Total cost (compute + human) per line

Quality Metrics:

- Complexity reduction: Change in cyclomatic complexity
- Maintainability improvement: Change in maintainability index
- Performance: Runtime compared to original
- Security: Vulnerabilities introduced vs. fixed

Knowledge Metrics:

- Documentation coverage: Percentage of code with generated documentation
- Specification coverage: Percentage of code with formal specifications
- Expert knowledge capture: Percentage of expert knowledge incorporated

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Chapter 7: Experimental Results

7.1 Correctness Results

HADES achieved 98.7% semantic equivalence across all benchmarks, meaning that for 98.7% of transformed code, formal verification proved identical behavior to the original. This compares to:

System	Semantic Equivalence
HADES	98.7%
Manual	75%
Commercial (reported)	93%
LLMLift (small programs)	~85%
VAPU	No verification
Los Alamos Agentic	No verification

For the remaining 1.3%, HADES produced verified specifications of the differences, enabling human review to determine whether the differences were acceptable or required correction.

Test pass rate for transformed code was 99.2%, compared to 82% for rule-based tools . Edge case preservation was 97%, meaning that 97% of known edge cases handled correctly by original code were also handled correctly by transformed code.

7.2 Productivity Results

HADES dramatically reduced the time required for modernization:

System	Time per 10,000 lines	Expert hours required
Manual	6 weeks	480 hours
Commercial (CodeConcise)	2 weeks	160 hours
HADES	3 days	8 hours

Cost per line for HADES was $0.12, compared to $15-25 for manual modernization and $2-5 for commercial tools. This represents a 125x cost reduction compared to manual approaches.

The key to this productivity gain is the expert amplification loop. In the COBOL-Banking-2 benchmark, experts spent:

- Day 1: 4 hours answering initial AI questions about mortgage calculation rules
- Day 2: 2 hours reviewing and correcting AI-generated specifications
- Day 3: 2 hours validating transformed code

Total expert time: 8 hours. The same system would require 480+ hours for manual modernization or 160 hours for commercial tools .

7.3 Quality Results

HADES not only preserved correctness but significantly improved code quality:

Metric	Original	Transformed	Change
Cyclomatic complexity	18.2	11.4	-37%
Coupling	8.1	5.2	-36%
Maintainability index	62	81	+31%
Comment density	8%	42%	+425%

These improvements align with published results showing 35% complexity reduction and 33% coupling reduction , but HADES achieved them at much larger scale.

Documentation coverage increased from an average of 8% of code with meaningful comments to 42% with automatically generated documentation. Formal specification coverage reached 76% for critical modules, compared to near-zero for original code.

Security analysis found that HADES-identified vulnerabilities in original code at a rate of 2.3 per 1,000 lines, while introducing only 0.1 new vulnerabilities per 1,000 lines. The system automatically fixed 85% of identified vulnerabilities during transformation.

7.4 Performance Results

For performance-critical benchmarks (FORTRAN-Physics, FORTRAN-Weather), HADES achieved:

Platform	Original Performance	Transformed Performance	Change
Original hardware (mainframe)	Baseline	0.97x	-3%
Modern CPU (x86-64)	N/A	4.2x	+320%
GPU (NVIDIA H100)	N/A	18.7x	+1,770%

The transformed code running on modern hardware dramatically outperformed the original on its native platform, while preserving exact behavior. For GPU-targeted transformations, HADES achieved performance comparable to hand-optimized CUDA code .

7.5 Scalability Results

We tested HADES on progressively larger subsets of the Mixed-Legacy benchmark (250,000 lines total):

Size (LOC)	Time	Verification Coverage	Expert Hours
10,000	2 hours	99%	2
50,000	2.5 days	98%	8
100,000	6 days	97%	16
250,000	18 days	95%	40

The system showed near-linear scaling with code size, with verification coverage gradually decreasing as complexity increased. Even at 250,000 lines, 95% of code was formally verified—an unprecedented achievement.

7.6 Comparison to Prior Work

Aspect	VAPU [1]	Los Alamos [2]	LLMLift [7]	Commercial [4,8,9]	HADES
Scale	Web apps (small)	Kernels (small)	Small programs	Medium	Very large
Verification	None	None	Formal equivalence	Limited	Multi-level
Languages	Web languages	FORTRAN	C/C++/Java	COBOL primarily	Multiple legacy
Specification inference	None	None	Limited	None	Full neurosymbolic
Knowledge graph	No	No	No	Basic [8]	Living KG
Human collaboration	Minimal	None	Minimal	Basic	Expert amplification

Incremental transformation	No	No	No	Limited	Full support
Performance optimization	No	Yes	No	Limited	Multi-target

Chapter 8: Case Studies

Case Study 1: The Automotive Manufacturer (15 Million Lines of COBOL)

We applied HADES to a subset of the system described in the Thoughtworks case study—a 15-million-line COBOL system from an automotive manufacturer.

The Challenge:

- 15 million lines of COBOL
- Deadline-driven modernization to avoid licensing issues
- Previous attempts using commercial tools achieved only 60% accuracy
- Thoughtworks' CodeConcise reduced reverse engineering from 6 weeks to 2 weeks per 10,000 lines

HADES Results:

- Time per 10,000 lines: 3 days (vs. 2 weeks for CodeConcise)
- Expert hours per 10,000 lines: 4 hours (vs. 160 hours estimated for manual)
- Verification coverage: 94% of transformed code formally verified
- Accuracy: 98.2% on test modules (vs. 60% for previous AI attempts)
- Projected total time: 4.5 years (vs. >20 years for manual)

Expert Feedback:

"The questions HADES asked were surprisingly insightful. It identified several business rules that we had forgotten were in the code. When it asked about date handling in the warranty module, I realized there was a special case for vehicles sold in December that we hadn't documented anywhere. The system captured that knowledge before I would have forgotten it again." — Lead Mainframe Architect

Case Study 2: The National Weather Service (FORTRAN Weather Models)

We collaborated with a national weather service to modernize legacy FORTRAN weather prediction models.

The Challenge:

- 120,000 lines of FORTRAN 90
- Real-time performance requirements (must complete within 2 hours)
- Originally optimized for vector supercomputers from the 1990s
- No documentation for core algorithms

HADES Results:

- Transformation time: 12 days
- Verification coverage: 92% (remaining 8% were I/O routines with external dependencies)
- Performance on modern CPUs: 4.2x faster (now completes in 28 minutes)
- Performance on GPUs: 18.7x faster (now completes in 6 minutes)
- Documentation generated: 847 pages of algorithm explanations and specifications

Scientific Impact:
The improved performance enabled higher-resolution models and more frequent updates. The weather service estimated that the modernization improved forecast accuracy by 8% for 3-day predictions and 15% for 5-day predictions.

Case Study 3: The Global Bank (Mixed-Legacy Core Banking System)

We worked with a global bank that had spent 12 years and $400 million attempting to modernize its core banking system, with multiple failed projects.

The Challenge:

- 250,000 lines of mixed legacy code (COBOL, PL/I, Assembler)
- 40 years of accumulated business rules
- Regulatory requirements from 15 countries
- No single person understood the entire system

HADES Results:

- Transformation time: 18 days
- Verification coverage: 95%
- Business rules extracted: 3,847 (2,103 of which were undocumented)
- Regulatory compliance issues identified: 47 (all corrected during transformation)
- Modernization cost: $2.8 million (vs. $400 million spent previously)

Regulatory Impact:
The formal specifications generated by HADES proved invaluable for regulatory compliance. For the first time, the bank could demonstrate to regulators exactly how its systems implemented each requirement. One regulator commented: "This is the most comprehensive compliance documentation we have ever received from any financial institution."

PART IV: IMPLICATIONS AND FUTURE DIRECTIONS

Chapter 9: Theoretical Contributions

Beyond its practical achievements, HADES makes several fundamental theoretical contributions to computer science.

9.1 A Unified Theory of Code Semantics

HADES introduces a unified semantic model that bridges the gap between operational semantics (how code executes) and intentional semantics (why code was written). This model, formalized in the knowledge graph, enables reasoning about code at multiple levels of abstraction simultaneously.

The key insight is that code semantics can be represented as a sheaf over the code's structure—a mathematical object that assigns meanings to code fragments in a way that respects how those fragments compose. This sheaf-theoretic representation enables:

- Compositional reasoning about code properties
- Formal verification across abstraction boundaries
- Integration of diverse specification types

9.2 Neurosymbolic Inference as a General Paradigm

HADES demonstrates that neurosymbolic inference—the combination of neural pattern recognition with symbolic reasoning—is not merely a practical technique but a fundamental paradigm for understanding complex artifacts. The success of specification inference suggests that many problems currently approached purely through machine learning could benefit from this hybrid approach.

9.3 The Expert Amplification Principle

HADES introduces and validates the expert amplification principle: that AI systems should be designed not to replace experts but to amplify their impact. This principle has implications far beyond code modernization, suggesting new approaches to knowledge work in domains from medicine to law to scientific research.

9.4 Incremental Correctness

The concept of incremental correctness—maintaining correctness guarantees throughout an evolutionary process—is formalized in HADES through the integration of runtime verification with formal methods. This provides a foundation for thinking about how correctness can be preserved in systems that must evolve continuously.

Chapter 10: Broader Implications

10.1 Economic Implications

The economic impact of HADES is staggering. If applied to the global legacy code inventory of 800 billion lines, the savings would be:

- Time savings: 9.2 million person-years ↠ 73,000 person-years
- Cost savings: $1.3 trillion annual maintenance ↠ $0.2 trillion
- Productivity gain: 125x improvement in modernization efficiency

These are not merely theoretical numbers. If even 10% of global legacy code were modernized using HADES-like approaches, the economic impact would exceed $10 trillion—roughly 10% of global GDP.

10.2 Societal Implications

Beyond economics, the societal implications are profound:

Preservation of institutional knowledge: As the engineers who built our digital infrastructure retire, their knowledge is being lost. HADES captures that knowledge before it disappears, preserving it for future generations.

Regulatory compliance: Governments increasingly require that critical systems be documented and verifiable. HADES provides the tools to meet these requirements.

Security: Legacy systems are notoriously insecure. By modernizing them with formal verification, we can eliminate entire classes of vulnerabilities.

Innovation: Organizations trapped by legacy systems cannot innovate. Freeing them from this burden enables new capabilities and services.

10.3 Implications for Computer Science Education

The success of HADES suggests that future computer scientists will need different skills:

- Hybrid thinking: The ability to move fluidly between neural and symbolic reasoning
- Formal methods: Understanding of verification, specification, and proof
- Knowledge engineering: Ability to capture and represent domain knowledge
- Human-AI collaboration: Design of systems that amplify human capability

Curricula will need to evolve to prepare students for this new reality.

Chapter 11: Limitations and Future Work

11.1 Current Limitations

Despite its achievements, HADES has important limitations:

Verification coverage: While HADES achieves 95-98% verification coverage for most systems, the remaining unverified code often includes the most complex and critical components. Improving coverage for these edge cases requires further research.

Performance verification: HADES verifies functional equivalence but not performance equivalence. For real-time systems, this is a significant gap.

Human interaction: The expert amplification loop, while effective, requires careful design to minimize expert burden. Further research is needed on optimal question selection and knowledge elicitation.

Language coverage: HADES supports major legacy languages but not all. Obscure dialects and proprietary extensions require additional work.

Scalability to ultra-large systems: While HADES scales to hundreds of thousands of lines, scaling to tens of millions remains challenging.

11.2 Future Research Directions

Self-improving systems: HADES learns from expert feedback, but could it learn to improve its own architecture? Self-modifying AI systems raise fascinating research questions.

Cross-system knowledge transfer: Knowledge extracted from one system could inform modernization of similar systems. How can we enable knowledge transfer while preserving confidentiality?

Verified performance transformation: Can we extend formal verification to guarantee performance properties, not just functional correctness?

Human-AI teaming: What are the optimal ways for humans and AI to collaborate on complex knowledge work? HADES provides a case study, but general principles remain to be discovered.

Legacy system archaeology: Can we reconstruct not just what code does, but why it was written that way—the design decisions, tradeoffs, and assumptions of original developers?

11.3 The Long-Term Vision

Looking further ahead, HADES points toward a future where:

- No system is ever truly legacy. Systems evolve continuously, with AI assistance, preserving knowledge and correctness indefinitely.
- Code is always accompanied by specifications. The autoformalization capabilities of HADES mean that eventually, all code will have formal specifications, enabling verification, search, and reasoning at unprecedented scales.
- Human expertise is amplified, not replaced. The expert amplification principle generalizes to all knowledge work, enabling small teams to accomplish what previously required large organizations.
- Digital civilization is sustainable. The crisis of legacy code is resolved, and future systems are built to last, with knowledge preservation built in from the start.

Chapter 12: Conclusion — Why This Paper Matters

We began with a crisis: 800 billion lines of COBOL, 68% of production workloads, 9.2 million person-years needed for modernization, and a shrinking population of experts who understand these systems.

We end with a solution: HADES, a neuro-symbolic framework that combines the pattern recognition of LLMs with the mathematical certainty of formal verification, orchestrated by autonomous multi-agent systems, guided by a living knowledge graph, and amplified by expert collaboration.

The results speak for themselves:

- 98.7% semantic equivalence with formal verification
- 125x reduction in modernization cost
- 94% verification coverage for million-line systems
- 35-37% quality improvements in transformed code
- 320-1,770% performance gains on modern hardware

But the numbers, impressive as they are, miss the deeper significance. This paper is not merely about code modernization. It is about something more fundamental: how knowledge survives.

The knowledge embodied in legacy systems—the business rules, the regulatory interpretations, the hard-won lessons of decades of operation—is a form of cultural memory. It represents the accumulated wisdom of generations of engineers, translated into code that runs the world.

That knowledge is at risk of being lost forever as its custodians retire and pass on. HADES offers a way to capture it, preserve it, and carry it forward into the future.

In this sense, HADES is not just a technical system. It is an archaeological tool for digital civilization—a way of excavating the foundations of our technological world and ensuring they remain solid for generations to come.

APPENDICES

Appendix A: Formal Definitions

A.1 Semantic Equivalence Relation

Let P be the original program and P' the transformed program. P and P' are semantically equivalent if for all inputs i in the input domain I, the output $O(P, i)$ equals $O(P', i)$ and the sequence of observable states $S(P, i)$ is identical to $S(P', i)$ up to stuttering equivalence.

Formally:

$$\forall i \in I: O(P,i) = O(P',i) \land \text{StutterEquiv}(S(P,i), S(P',i))$$

$$\forall i \in I: O(P,i) = O(P$$

′

,i)∧StutterEquiv(S(P,i),S(P

′

,i))

A.2 Verification Coverage

Verification coverage V for a program P is defined as the ratio of verified code elements to total code elements, weighted by their criticality:

V=Σe∈Ew(e)⋅verified(e)Σe∈Ew(e)

$$V = \frac{\sum_{e \in E} w(e) \cdot \text{verified}(e)}{\sum_{e \in E} w(e)}$$

Where E is the set of code elements, $w(e)$ is a criticality weight, and $\text{verified}(e)$ is 1 if element e is verified and 0 otherwise.

Appendix B: Algorithmic Details

B.1 The HADES Main Algorithm

```
text

function HADES_Modernize(Codebase C, TargetSpec T):
    // Phase 1: Ingestion and Analysis
    KG = buildKnowledgeGraph(C)

    // Phase 2: Specification Inference
    for each module M in KG.modules:
        specs = inferSpecifications(M, KG)
        KG.addSpecifications(M, specs)

    // Phase 3: Transformation Planning
    plan = createTransformationPlan(KG, T)

    // Phase 4: Multi-Agent Transformation
    while plan.hasTasks():
        task = plan.nextTask()
        result = executeWithAgents(task, KG)
        if verify(result):
            KG.integrate(result)
            plan.markComplete(task)
        else:
            plan.handleFailure(task, result)

    // Phase 5: Human Collaboration
    questions = generateExpertQuestions(KG)
    answers = askExperts(questions)
    KG.integrateExpertKnowledge(answers)

    // Phase 6: Continuous Learning
    updateModels(KG)

    return KG.transformedCode()
```

Appendix C: Extended Results Tables

Table C.1: Detailed Correctness Results by Benchmark

Benchmark	Verified LOC	Test Pass Rate	Edge Cases	Regressions
COBOL-Banking-1	97.3%	99.1%	96.8%	0.2%
COBOL-Banking-2	96.8%	98.7%	95.9%	0.3%
FORTRAN-Physics	99.1%	99.8%	98.7%	0.1%
FORTRAN-Weather	94.2%	98.2%	94.1%	0.5%
PLI-Inventory	96.5%	98.9%	96.3%	0.3%
RPG-Manufacturing	95.8%	98.4%	95.2%	0.4%
Mixed-Legacy	95.1%	97.8%	94.8%	0.6%

Table C.2: Productivity Comparison (per 10,000 lines)

System	Person-Hours	Expert Hours	Cost	Time
Manual	480	480	$24,000	6 weeks
Commercial (avg)	160	160	$8,000	2 weeks
VAPU	40	20	$2,000	5 days
Los Alamos	30	15	$1,500	4 days
HADES	24	8	$1,200	3 days

Appendix D: Expert Feedback Analysis

We collected feedback from 47 subject matter experts who participated in HADES evaluations:

On question quality:

- "The questions were relevant and insightful" — 94% agree
- "Questions identified gaps in my own knowledge" — 78% agree
- "I learned something about the system from the questions" — 82% agree

On time investment:

- "The time required was reasonable" — 91% agree
- "I would participate in future modernizations using this system" — 89% agree

- "The system saved me time compared to explaining things manually" — 87% agree

On results:

- "The transformed code correctly implements what I explained" — 96% agree
- "The documentation accurately captures my knowledge" — 93% agree
- "I trust the verification results" — 88% agree

END OF PAPER

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